



Paris School of AI - PSL

SYLLABUS

Master's Degree AI & Society

Academic Year 2025-2026

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Course: Data structures and programming in Python

Instructor: Emiliano Lancini

Bio: Emiliano Lancini is a Maître de Conférences at Université Paris-Dauphine – PSL. His research focuses on combinatorial optimization, with a particular interest in the polyhedral properties of graph optimization problems. He obtained his PhD in 2019 from Sorbonne Paris Nord with a thesis entitled TDIness and Multicuts. At Dauphine, he teaches courses in computer science, including Python programming and graph theory.

Webpage: <https://www.lamsade.dauphine.fr/~elancini/eng.html>

Course Description: This course offers an introduction to programming in Python with a focus on fundamental data structures and their applications. Designed as a refresher, it assumes varied backgrounds and aims to establish a common foundation for students entering the AI & Society master program. The first part of the course reviews essential elements of Python programming, including variables, functions, control structures, and the use of core data types. Building on this basis, the course introduces the concepts of recursion and algorithmic thinking, highlighting the intuitive distinction between efficient and inefficient approaches to problem solving. Students will gain experience in handling data through the use of Python tools for data processing, cleaning, and visualization. In the final part of the course, students will apply their knowledge to implement some classic algorithms from scratch in order to understand how data structures and programming constructs translate into concrete analytical methods. Throughout the course, hands-on exercises will allow participants to strengthen their coding skills.

Hourly Volume : 12

Skills to be Acquired:

- Students will acquire and solidify knowledge of fundamental Python programming concepts and core data structures.
- They will develop algorithmic thinking and learn to design solutions using clear and efficient code.
- They will also gain practical experience implementing classic algorithms and managing data in structured forms.

Bibliography/Recommended Reading: There course is self-contained, however the classic book Mark Lutz – Learning Python (O'Reilly Media) can be used as a complement to this course for a richer and more gentle introduction to the Python language.

Course: Social sciences and behavioral sciences (game theory and evolution, cognitive and social psychology, collective behaviors)

Instructor: Nicolas Baumard

Bio: Nicolas Baumard is an evolutionary and cognitive social scientist working in the Evolution and Social Cognition team at Institut Jean-Nicod at ENS-PSL. He draws on cognitive science, behavioral ecology, and evolutionary biology to explain why cultural phenomena emerge, spread, and evolve.

Webpage: <https://nicolasbaumards.org/>

Course Description: This course provides an integrative introduction to the study of human behavior and societies, combining insights from evolutionary biology, behavioral ecology, cognitive psychology, and the social sciences. Students will be introduced to the key mechanisms shaping human behavior, such as life history strategies, conditional cooperation, signaling, and adaptive plasticity, and will learn how these mechanisms interact with cultural variation, ecological conditions, and social institutions. A central theme of the course is the interplay between ultimate explanations rooted in evolutionary fitness and proximate explanations focused on cognitive processes. Drawing on examples from anthropology, psychology, and economics, we will explore how humans cooperate, build institutions, and transmit culture. The course will also address the effects of poverty, inequality, and environmental variability on preferences and personalities, as well as the emergence of moral systems and religious beliefs. Throughout, case studies on issues such as climate change, vaccine hesitancy, and school drop-out will illustrate how these theories apply to contemporary challenges. The flipped-classroom format emphasizes active student engagement with readings and discussion, enabling participants to develop both conceptual mastery and critical perspectives on the evolution of human behavior and culture.

ECTS : 6

Hourly Volume : 48

Skills to be Acquired:

By the end of the course, you will be able to analyze human behavior through an integrative framework combining evolutionary, cognitive, and cultural perspectives. You will master key concepts in behavioral ecology and evolutionary psychology, such as life history strategies, cooperation, and signaling. You will learn to critically evaluate how ecological variability, poverty, and institutions shape social structures and cultural change. You will apply these theories to pressing issues like climate change, vaccine hesitancy, and educational

inequalities. You will strengthen your skills in critical reading, interdisciplinary analysis, and scientific writing through active discussion and case studies.

Bibliography/Recommended Reading: Boyer, P. (2020). Minds make societies: How cognition explains the world humans create. Yale University Press.

CORE Team, The (2017). The Economy, Economics for a Changing World. Oxford: Oxford University Press. Open access : <https://www.core-econ.org/>

Nettle, D. (2009). Evolution And Genetics For Psychology. Oxford: Oxford University Press.

Chevallier, C., & Perona, M. (2022). Homo sapiens dans la cité: comment adapter l'action publique à la psychologie humaine. Odile Jacob.

Diamond, J. (1997). Guns. Germs and Steel: The Fates of Human Societies, Vintage, 186.

Course: Foundations of supervised and unsupervised machine learning

Instructor: Frédéric LECHENAULT

Bio: Experimental physicist at LPENS, DR at CNRS, I've worked on various table-top situations exhibiting interesting shape or collective behavior, including granular materials, origamis, knitted fabric, breaking and cutting soft materials... I've also resorted to reinforcement learning with artificial neural networks to gain valuable insights into this area of physics.

Webpage: <https://www.lpens.ens.psl.eu/frederic-lechenault/>

Course Description: This twelve-session course provides a rigorous, practice-oriented introduction to machine learning for first-year Master's students. Each two-hour meeting combines a concept-driven lecture with a guided Python lab. We begin by formalizing prediction through loss functions, empirical risk, and disciplined train-validation-test procedures. Linear regression is developed from first principles and extended with regularization and careful feature engineering to manage variance and collinearity. Binary classification is introduced via the logistic model, emphasizing threshold selection under asymmetric costs and class imbalance. Sound evaluation is a recurring theme, with stratified cross-validation, bootstrap confidence intervals, and permutation methods to quantify uncertainty and test relevance. Optimization is treated as the engine of learning, focusing on gradient descent and its stochastic variant. Nonlinear modeling is addressed through ensembles (bagging and boosting) and vanilla neural networks, with attention to overfitting control and feature importance. Foundational treatment of time series covers temporal splitting, seasonal and naive baselines, lag construction, and simple autoregression. A parallel treatment of text data introduces tokenization, bag-of-words representations,

weighting schemes, and linear classifiers. Unsupervised learning is surveyed through clustering by means and principal component analysis for structure discovery and visualization. The course concludes with decision-making under uncertainty (multi-armed

bandits), reinforcement learning (Q-learning), and overview of metaheuristics, with a hands-on simulated-annealing lab.

ECTS : 3

Hourly Volume : 24

Skills to be Acquired:

Formulate prediction problems and choose appropriate loss functions; reason about empirical risk and generalization. Design honest data splits (train/validation/test, temporal splits) and prevent information leakage. Build, tune, and interpret linear models for regression and classification, including regularization and safe feature engineering. Set decision thresholds under asymmetric costs and class imbalance; interpret calibrated probabilities. Evaluate models rigorously with stratified cross-validation, bootstrap confidence intervals, and permutation tests for relevance. Optimize model parameters via gradient descent and mini-batch stochastic gradient descent; diagnose learning-rate issues. Use ensemble methods (bagging and boosting) to reduce variance/bias and read feature-importance reports. Apply unsupervised techniques: run k-means responsibly and use principal component analysis for dimensionality reduction and visualization. Model simple time series: implement seasonal and naive baselines, create lag/seasonal features, and run walk-forward validation. Process text data: tokenize, build bag-of-words with term-frequency-inverse-document-frequency weighting, add n-grams, and train linear text classifiers. Understand bandit-style decision making: implement and compare exploration strategies such as epsilon-greedy. Learn to play a simple game with Q-learning. Solve small combinatorial problems with simulated annealing; compare solution quality under time budgets. Work reproducibly in Python: use pipelines, scaling, and clear experiment logs; communicate results with plots and short memos.

Bibliography/Recommended Reading: Core texts • Hastie, Tibshirani, Friedman. The Elements of Statistical Learning. 2nd ed., Springer, 2009. • Murphy, Kevin P. Probabilistic Machine Learning: An Introduction. MIT Press, 2022. • Bishop, Christopher M. Pattern Recognition and Machine Learning. Springer, 2006. • James, Witten, Hastie, Tibshirani. An Introduction to Statistical Learning (with Python companion). Springer, 2021–2023.

Practical, Python-first • Geron, Aurelien. Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow. 3rd ed., O'Reilly, 2022. • McKinney, Wes. Python for Data Analysis. 3rd ed., O'Reilly, 2022. • Pedregosa et al. "Scikit-learn: Machine Learning in Python." JMLR, 2011.

Evaluation and uncertainty • Efron, Bradley; Tibshirani, Robert. An Introduction to the Bootstrap. CRC, 1993. • Good, Philip. Permutation Tests: A Practical Guide to Resampling Methods for Testing Hypotheses. 3rd ed., Springer, 2005.

Optimization fundamentals • Nocedal, Jorge; Wright, Stephen. Numerical Optimization. 2nd ed., Springer, 2006. • Boyd, Stephen; Vandenberghe, Lieven. Convex Optimization. Cambridge University Press, 2004 (free online).

Ensembles: Random Forests & Boosting • Breiman, L. (2001). "Random Forests." Machine Learning. (Foundational paper; methodology and theory.) • Biau, G.; Scornet, E. (2016). "A Random Forest Guided Tour." TEST. (Clear survey of consistency and mechanisms.) • Friedman, J. H. (2001). "Greedy Function Approximation: A Gradient Boosting Machine." Annals of Statistics. (The classic gradient boosting paper.) • Freund, Y.; Schapire, R. (1997/1999). "A Decision-Theoretic Generalization of On-Line Learning..." / "A Short Introduction to Boosting." (AdaBoost foundations and intuition.) • Chen, T.; Guestrin, C. (2016). "XGBoost: A Scalable Tree Boosting System." KDD. (Engineering + regularization tricks.) • Ke, G. et al. (2017). "LightGBM: A Highly Efficient Gradient Boosting Decision Tree." NeurIPS. (Histogram-based, leaf-wise growth.) • Prokhorenkova, L. et al. (2018). "CatBoost: Unbiased Boosting with Categorical Features." NeurIPS. (Ordered boosting; leakage-resistant handling of categories.)

Neural Networks & Deep Learning • Goodfellow, I.; Bengio, Y.; Courville, A. (2016). Deep Learning. MIT Press. (Standard reference; theory + practice.) • Nielsen, M. A. (2015). Neural Networks and Deep Learning. (Gentle, math-light introduction; free online.) • LeCun, Y.; Bengio, Y.; Hinton, G. (2015). "Deep Learning." Nature. (Broad overview and historical context.) • Ioffe, S.; Szegedy, C. (2015). "Batch Normalization: Accelerating Deep Network Training." ICML. (Stabilizes training; ubiquitous.) • Srivastava, N. et al. (2014). "Dropout: A Simple Way to Prevent Neural Networks from Overfitting." JMLR. (Regularization staple.) • Kingma, D. P.; Ba, J. (2015). "Adam: A Method for Stochastic Optimization." ICLR. (Default optimizer in many setups.) • He, K. et al. (2016). "Deep Residual Learning for Image Recognition." CVPR. (Residual connections; very influential.) • Zhang, A. et al. (2023, updated). Dive into Deep Learning. (Hands-on text with code notebooks; free online.)



Unsupervised learning & dimensionality reduction • Shalev-Shwartz, Shai; Ben-David, Shai. Understanding Machine Learning: From Theory to Algorithms. Cambridge University Press, 2014 (concise chapters on clustering and principal components). Time series • Hyndman, Rob J.; Athanasopoulos, George. Forecasting: Principles and Practice. 3rd ed., OTexts, 2021 (free online). • Shumway, Robert H.; Stoffer, David S. Time Series Analysis and Its Applications. 4th ed., Springer, 2017.

Natural language processing • Jurafsky, Daniel; Martin, James H. Speech and Language Processing. 3rd ed. draft, Prentice Hall/OUP, ongoing (free online). • Bird, Steven; Klein, Ewan; Loper, Edward. Natural Language Processing with Python. O'Reilly, 2009.

Reinforcement learning • Sutton, Richard S.; Barto, Andrew G. Reinforcement Learning: An Introduction. 2nd ed., MIT Press, 2018 (free online).

Metaheuristics (overview level) • Luke, Sean. Essentials of Metaheuristics. 2nd ed., 2013 (free online). • Eiben, A. E.; Smith, J. E. Introduction to Evolutionary Computing. 2nd ed., Springer, 2015. • Dorigo, Marco; Stutzle, Thomas. Ant Colony Optimization. MIT Press, 2004.

Course: Microéconomie, Game theory (Remise en niveau)

Instructor: Lucas Eustache

Bio: Lucas Eustache has been a doctoral researcher at the Governance and Regulation Chair since the beginning of the 2022 academic year. He holds a Master's degree in Public Policy from the University of Paris 1 Panthéon-Sorbonne. His doctoral research focuses on the business models of data-sharing intermediaries.

Course Description: This course introduces students to the core analytical tools of microeconomics, game theory, and competition economics, with a strong emphasis on practical intuition and policy relevance. The first session covers the foundations of microeconomics, including scarcity, opportunity cost, and incentives, before moving into supply and demand, elasticity, welfare analysis, and key market failures. It also highlights modern extensions such as platforms, data, and behavioral biases that shape real-world decision-making. The second session turns to game theory, providing a framework for understanding strategic interactions among economic agents. Students are introduced to concepts such as dominance, best responses, and Nash equilibrium, as well as dynamic and incomplete-information games. Applications include classical dilemmas, mixed strategies, and auctions, with insights into how strategies evolve in competitive and uncertain environments. The third session focuses on markets with power and the economics of regulation. It examines oligopoly models, market definition tools, and the legal-economic



framework governing dominance, collusion, and exclusionary practices under EU competition law. Barriers to entry, both natural and strategic, are explored alongside remedies and policy instruments, including competition policy, regulation, and behavioral interventions. Overall, the course equips students with a structured understanding of how markets function, where they fail, and how economic reasoning informs both business strategy and public policy.

Hourly Volume : 12

Skills to be Acquired: By the end of the three meetings, you should be able to: Explain foundational micro ideas (scarcity, opportunity cost, marginal thinking; supply, demand, elasticity) and use them to reason about prices, quantities, and welfare. Diagnose classic market failures (externalities, public goods, market power, information problems) and sketch policy levers (Pigouvian tools, standards, antitrust, information remedies). Define games, strategies, and equilibria; identify dominance and Nash equilibria; reason about mixed strategies and extensive-form (sequential) settings. Connect oligopoly models

(Cournot vs. Bertrand), market definition (SSNIP), dominance/abuse, and barriers to entry to real-world tech/platform market

Bibliography/Recommended Reading: The following textbooks can provide additional background information for the material covered in this course: Varian: Intermediate Microeconomics: A Modern Approach

https://www.academia.edu/40718586/INTERMEDIATE_MICROECONOMICS_HAL_VARIAN
Osborne: An Introduction to Game Theory (<https://global.oup.com/academic/product/an-introduction-to-game-theory-9780195128956>)

Course: Big Data paradigms

Instructor: Dario Colazzo

Bio: Dario Colazzo is a Professor at Université Paris-Dauphine and PSL, as well as a part-time professor at Ecole Polytechnique, and a fellow of PRAIRIE-PSAI. He has been the main actor in the creation of the Data Science team at LAMSADE, which he led from 2015 to 2020. He is director of the Executive Master IASD at Dauphine-PSL. His main research interests focus on static analysis techniques for large-scale data management, and LLM-driven synthetic data generation.

Webpage: <https://dauphine.psl.eu/recherche/cvtheque/profil/colazzo-dario>

Course Description: This course provides students with comprehensive knowledge and understanding of big data processing technologies, starting from distributed computing fundamentals and progressing to advanced algorithm implementation in Apache Spark. The

course is divided into two main parts: foundational concepts in distributed systems and MapReduce programming, followed by in-depth coverage of Spark for complex data processing applications. The first part introduces students to cluster architectures, distributed file systems (particularly HDFS), and the MapReduce programming model. Students will understand the principles of distributed computing, fault tolerance

mechanisms, and how to design algorithms that can scale across multiple machines. The second part focuses extensively on Apache Spark, covering both fundamental concepts and advanced optimization techniques. Students will learn to implement sophisticated algorithms for text processing, SQL-based data analysis, graph processing, and iterative machine learning algorithms including gradient descent and clustering techniques. Special emphasis is placed on performance optimization, memory management, and the design of efficient distributed algorithms.

ECTS : 3

Hourly Volume : 24

Skills to be Acquired: Students will master the MapReduce programming paradigm and understand distributed file system architectures. They will develop expertise in Apache Spark programming, including RDD manipulation, DataFrame operations, and the implementation of complex algorithms for various domains. The course emphasizes practical skills in optimizing Spark applications for performance and scalability, enabling students to tackle real-world big data challenges.

Bibliography/Recommended Reading: - Mining of Massive Datasets,. Jure Leskovec, Anand Rajaraman, Jeff Ullman. www.mmids.org - Data-Intensive Text Processing with MapReduce. Jimmy Lin and Chris Dyer University of Maryland. - High Performance Spark - Best Practices for Scaling and Optimizing Apache Spark Holden Karau, Rachel Warren O'Reilly

Course: Advanced programming

Instructor: Dario Colazzo, Nour El Houda Ben Ali

Bio: Dario Colazzo is a Professor at Université Paris-Dauphine and PSL, as well as part-time professor at Ecole Polytechnique, and a fellow of PRAIRIE-PSAI. He has been the main actor in the creation of the Data Science team at LAMSADE, which he led from 2015 to 2020. He is director of the Executive Master IASD at Dauphine-PSL. His main research interests focus on static analysis techniques for large-scale data management, and LLM-driven synthetic data generation.

Nour El Houda Ben Ali is a PhD candidate at LAMSADE, Dauphine University - PSL. Her research activities focus on static analysis for JSON Schema, as well as schema-driven synthetic JSON data generation using large language models. Her teaching activities focus on programming, semi-structured data, and machine learning.

Webpage: <https://dauphine.psl.eu/recherche/cvtheque/profil/colazzo-dario>

Course Description: This course develops solid programming skills in Python with a focus on data structures and algorithms essential for data science and management applications, including distributed computing principles and paradigms for handling large-scale datasets, playing a crucial role in AI applications. The course covers advanced iteration techniques, efficient hash map implementations, priority queue structures for handling complex datasets, as well as the application of Map-Reduce patterns for parallel data processing. Core topics include optimized sorting algorithms, strategic caching mechanisms, memory management techniques, the MapReduce paradigm and how implementing workflows in Python for processing complex and large-scale datasets.

ECTS : 3

Hourly Volume : 24

Skills to be Acquired: Through hands-on lab sessions and projects, students will learn to design and implement high-performance Python solutions that effectively manage memory resources while maintaining, code clarity, robustness and computational efficiency.

Bibliography/Recommended Reading: Data Structures and Algorithms in Python. Michael T. Goodrich, Roberto Tamassia, and Michael H. Goldwasse. Wiley.

Data-Intensive Text Processing with MapReduce Jimmy Lin, Chris Dyer.

Course: Databases and SQL

Instructor: Maude Manouvrier

Bio: Maude Manouvrier is currently working as Lecturer at the LAMSADE Lab. of Université Paris-Dauphine, PSL Research University. She has received a Ph.D. in Computer Science in 2000 and her Post Doctoral Degree (Habilitation à diriger des recherches in french) in 2016. Her research interests focused on Database and Knolwedge Graphs.

Webpage: <https://www.lamsade.dauphine.fr/en/people/detail-cv/profile/maude-manouvrier.html>

Course Description: Module Objectives This module introduces students to the design, manipulation, and querying of relational databases, with a focus on SQL (Structured Query Language), the standard language for relational database management.

Course Content Students will learn: (1) how to define relational database schemas; (2) how to formulate queries in Relational Algebra to understand DBMS query processing; and (3) how to create, manipulate, and query relational databases in SQL, including schema

definition, query writing, trigger implementation, and an introduction to query optimization.

Teaching Methods The module combines lectures with slide presentations, tutorial exercises on the relational model and Relational Algebra, and computer-based laboratory sessions on relational algebra and SQL.

Hourly Volume : 12

Skills to be Acquired: At the end of this module, students will have developed the following skills:

Ability to design relational database schemas that meet consistency and integrity requirements.

Proficiency in formulating and executing queries using both Relational Algebra and SQL.

Competence in implementing triggers and applying basic principles of query optimization.

Practical skills in manipulating and managing relational databases with a DBMS.

Critical understanding of how relational DBMSs process and evaluate queries.

Bibliography/Recommended Reading: A. Silberschatz, H.F. Korth et S. Sudarshan, Database System Concepts, McGraw-Hill, 7ème édition, 2019, ISBN: 978-0073523323

Beaulieu, A. (2020). Learning SQL: Generate, manipulate, and retrieve data. O'Reilly Media.

<https://sqlbolt.com/>

<https://www.postgresql.org/docs/current/index.html>

Course: Practical Machine Learning

Instructor: Davide Carbone

Bio: I am currently a Postdoctoral Fellow in AI at PSL, based at CSD-ENS. Previously I got my PhD in applied mathematics in Politecnico di Torino (Italy). My main interests is

nonequilibrium statistical physics and its interplay with the problem of sampling in scientific ML, and with foundations of generative models.

Webpage: <https://davide-carbone.github.io/contact.html>

Course Description: This course is the applied counterpart to Foundations of Supervised and Unsupervised Machine Learning, designed to consolidate theoretical concepts through hands-on experimentation in Python. Structured laboratories and projects guide students in

implementing, testing, and comparing models on real and synthetic data, using tools such as NumPy, pandas, scikit-learn, and related libraries. In the supervised part, the course covers regression and classification, with attention to regularization, feature engineering, ensemble methods, and optimization techniques. Particular emphasis is placed on fair evaluation, resampling strategies, and the careful use of baselines and benchmarks to interpret model performance. Applications to time series and text data illustrate how domain-specific considerations shape the design of predictive workflows. In the unsupervised part, the focus shifts to clustering and dimensionality reduction, with practical sessions on k-means, principal component analysis, and related methods for structure discovery and visualization. Advanced topics such as reinforcement learning and metaheuristics are introduced to broaden the perspective on learning and optimization beyond the supervised–unsupervised dichotomy. The overall aim is to provide a coherent and practice-oriented view of machine learning, highlighting methodological breadth, the role of computational tools, and the importance of rigorous experimental design.

ECTS : 4

Hourly Volume : 24

Skills to be Acquired: By the end of the course, students will be able to design and carry out complete machine learning experiments using Python and its scientific ecosystem. They will gain practical competence in data preprocessing and feature engineering with pandas and NumPy, model implementation and evaluation with scikit-learn, and result visualization with matplotlib and related tools. They will learn to select and validate models using appropriate train/validation/test protocols, to compare methods against baselines, and to quantify uncertainty through resampling. Students will also acquire experience in applying machine learning to different data types, including time series and text, and in interpreting the output of clustering, dimensionality reduction, and ensemble techniques.

Bibliography/Recommended Reading: The following textbooks and online references will be used in the course: - Raschka, S., Liu, Y., Mirjalili, V. — Machine Learning with PyTorch and Scikit-Learn (Packt, 2022). - VanderPlas, J. — Python Data Science Handbook (O'Reilly, 2016, freely available online). - Scikit-learn documentation: <https://scikit-learn.org>

In preparation of the lecture, it is suggested to use the references provided in the course of Foundations of Supervised and Unsupervised Machine Learning.

Course: Professionnal conferences

Instructor: Simon Porcher

Bio: I am a full professor of Management at Université Paris Dauphine PSL. I study how cross-sector partnerships create value and respond to grand challenges, using large datasets. I have been recognized as one of the top 40 under 40 professors in management worldwide by Poets & Quants.

Webpage: <https://sites.google.com/site/simporcher/>

Course Description: The Professional Conferences module is designed to immerse students in the real-world challenges and opportunities of artificial intelligence through direct engagement with leading experts across sectors. Throughout the semester, students will attend a curated series of conferences led by guest speakers from academia, industry, government, and civil society. These sessions will explore the multifaceted dimensions of AI, including 1) business applications, regulatory frameworks, and legal perspectives. Each conference is followed by a moderated discussion and Q&A, encouraging students to critically engage with the speakers and reflect on the societal implications of AI.

ECTS : 3

Hourly Volume : 24

Skills to be Acquired: By the end of the course, students will be able to analyze and compare diverse professional perspectives on AI; understand the interplay between technological innovation and societal regulation; articulate informed positions on ethical, legal, and economic issues raised by AI.

Bibliography/Recommended Reading: Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2), 3–30.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, 33(2), 31–50.

Commission européenne. (2024). AI Act – Regulatory Framework for Artificial Intelligence.

Frey, C. B., & Osborne, M. A. (2013). *The Future of Employment: How Susceptible Are Jobs to Computerisation?* Oxford Martin School, University of Oxford.



Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, 14(1), 366–410.

Orlikowski, W. J., & Scott, S. V. (2015). The Algorithm and the Crowd: Considering the Materiality of Service Innovation. *MIS Quarterly*, 39(1), 201–216.

Schellmann, H. (2024). *The Algorithm: How AI Decides Who Gets Hired, Monitored, Promoted, and Fired and Why We Need to Fight Back Now*. Grand Central Publishing.

Course: Digital economics

Instructor: Eric Brousseau

Bio: Éric BROUSSEAU is professor of economics and management. He holds the ‘Governance and Regulation’ Chair and is the scientific director of the ‘Club des Régulateurs’. He is also the director of the PSL Institute for ‘Applied Computational Social Sciences’ (ACSS). He has been developing research on the digital transformation, both from an organizational and institutional perspectives, as well as on institutional frameworks favoring innovation and supporting knowledge transfers.

Webpage: <https://www.brousseau.info/>

Course Description: This course aims at teaching the fundamentals of the economics of the three pillars of the digital transformation. Digital technologies allow, first, to generate and market information goods at a very large scale. Second digital technologies are characterized by strong network effects that depends upon both interdependences among components and networks topology. Third digital technologies allow to substitute capital for labor in governance, changing its very nature and allowing radical innovations. The specificities of the marketing of information goods, of network effects and of digital governance explain pricing and competitive strategies in the digital era, as well as the essence of digital business models and their variations. The course is organized around 4 topics: Economics of information, Networks effects, Technology and Governance, New business models & Platforms.

ECTS : 3

Hourly Volume : 24

Skills to be Acquired: Principles behind the production, marketing and valuation of goods and services intensive in information and knowledge. - Understanding of the interactions between socio-economic and technical phenomena in the Internet era - Understanding processes of organizational changes supported by digital technologies. - Analytical methods to analyze and develop sustainable business models.



Bibliography/Recommended Reading: Agrawal, Ajay ; Gans, Joshua ; Goldfarb, Avi (eds), The Economics of Artificial Intelligence: An Agenda, Chicago University Press, 2019 Belleflamme, Paul ; Peitz, Martin. The Economics of Platforms : Concepts and Strategy. Cambridge University Press, 2021 Brousseau, Eric ; Curien, Nicolas (eds), Internet and Digital Economics Principles, Methods and Applications, Cambridge University Press, 2007 Shapiro, Carl ; Varian, Hal, Information Rules, A strategic guide to the network economy, Harvard Business School Press, 1999